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Sustainable Use of Groundwater May Dramatically Reduce Irrigated Production of Maize, Soybean, and Wheat

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Key Points:

- We integrate a crop model with satellite observations and survey data to simulate sustainable groundwater use for agriculture
- Optimistic sustainable groundwater use may decrease US irrigated production of maize, soybean, and winter wheat by 20%, 6%, and 25%
- Pessimistic sustainable groundwater use may decrease US irrigated production of maize, soybean, and winter wheat up to 45%, 37%, and 36%

Supporting Information:

Supporting Information may be found in the online version of this article.

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Abstract Groundwater extraction in the United States (US) is unsustainable, making it essential to understand the impacts of limited water use on irrigated agriculture. To improve this understanding, we integrated a gridded crop model with satellite observations, recharge estimates, and water survey data to assess the effects of sustainable groundwater withdrawals on US irrigated agricultural production. The gridded crop model agrees with satellite-based estimates of evapotranspiration ($R^2 = 0.68$), as well as survey data from the United States Department of Agriculture ($R^2 = 0.82$–0.94 for county-level production and 0.37–0.54 for county-level yield). Using the optimistic assumption that groundwater extraction equals effective aquifer recharge rate, we find that sustainable groundwater use decreases US irrigated production of maize, soybean, and winter wheat by 20%, 6%, and 25%, respectively. Using a more conservative assumption of groundwater availability, US irrigated production of maize, soybean, and winter wheat decreases by 45%, 37%, and 36%, respectively. The wide range of simulated losses is driven by considerable uncertainty in surface water and groundwater interactions, as well as accounting for the many aspects of sustainability. Our results demonstrate the vulnerability of US irrigated agriculture to unsustainable groundwater pumping, highlighting the difficulty of expanding or even maintaining irrigated food production in the face of climate change, population growth, and shifting dietary demands. These findings are based on reducing pumping by fallowing irrigated farmland; however, alternate pumping reduction strategies or technological advances in crop genetics and irrigation could produce different results.

Plain Language Summary Irrigated agriculture in the United States (US) is depleting groundwater in some regions, which will eventually reduce the amount of water available for growing crops. We used a computer model to assess the impacts of sustainable water use on US irrigated agriculture. We first compared simulated crop production and water use with observed data over 5 years to evaluate the accuracy of the computer model. Simulated yield and crop water use were in good agreement with reported yields from the United States Department of Agriculture and satellite evapotranspiration estimates. We then modeled different water restriction scenarios and found that under the most optimistic scenario, US production of irrigated maize, soybean, and winter wheat decreases by 20%, 6%, and 25%, respectively. However, under the most pessimistic scenario, US production of these irrigated crops will decrease by 45%, 37%, and 36%, respectively. Overall, our simulations of different water restriction scenarios show the vulnerability of US irrigated agricultural production to reduced groundwater pumping, and highlight the difficulty of expanding or even maintaining irrigated food production across the country.

1. Introduction

Groundwater extraction in much of the United States (US) is unsustainable (USDA, 2018; Dieter et al., 2018; Maupin et al., 2014; Reitz et al., 2017). Combined, the two major aquifers in the US, the High Plains and Central Valley, were depleted by approximately 12.5 and 3.1 km^3 per year between 2003 and 2013, respectively (Famiglietti, 2014). This depletion is equivalent to 15% of total US groundwater extraction in 2010 (Maupin et al., 2014). Between 2010 and 2015, groundwater withdrawals for irrigation increased by 16% (Dieter et al., 2018). This increase was primarily driven by four states, California, Arkansas, Nebraska, and Idaho, that already had substantial groundwater use for irrigation and further increased irrigation groundwater use by 26%–59% (Dieter et al., 2018).

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Overall, irrigation used 67% of total US groundwater extraction in 2015 (Dieter et al., 2018), and groundwater use exceeds groundwater recharge across 15% of the contiguous US (Reitz et al., 2017). Groundwater extraction for irrigation must substantially decrease for US agricultural production to be sustainable, but doing so would have a negative impact on both the US and world food supplies. The US is responsible for 36% of global maize production, 35% of global soybean production, and 8% of global wheat production (USDA, 2018). In the US, approximately 17% of total maize production comes from irrigated agriculture, as well as 12% of total soybean and wheat production (USDA-NASS, 2017). These three crops occupy 52% (maize 22%, soybean 17%, and wheat 13%) of US irrigated agricultural area (Dieter et al., 2018). The tension between increasing food production and using water sustainably raises two critical questions: how much groundwater can be extracted while still irrigating sustainably, and what would the impacts of irrigating sustainably be on agricultural production?

Multiple studies have approximated sustainable groundwater extraction for agriculture using the concept of safe aquifer yield (Hahn et al., 1997; Miles & Chambet, 1995; Voudouris, 2006). Safe aquifer yield is defined as the estimated sustainable groundwater extraction rate and based on aquifer recharge rates (Miles & Chambet, 1995). The safe aquifer yield over agriculturally intensive areas can be derived using a water balance approach, where the aquifer recharge rate is calculated from water inflows (precipitation and irrigation return) and outflows (runoff and evapotranspiration; Reitz et al., 2017). Aquifer recharge rates are highly dependent on future precipitation, but future precipitation and drought are difficult to predict (Patricola & Cook, 2013; Winter et al., 2015). Therefore, safe aquifer yields are typically set below recharge rates, and can vary based on approach (Reitz et al., 2017). For example, Miles and Chambet (1995) proposed a conservative safe aquifer yield of 10% of recharge, while Hahn et al. (1997) estimated more optimistic safe aquifer yields between 36% and 75% of recharge for different areas depending on elevation.

However, Bredehoeft (2002) and others note a fundamental flaw with the idea that recharge can be directly linked to sustainable groundwater development. Mainly, that the use of recharge alone largely neglects groundwater hydrology, which is crucial to determining how much water a well can access (Bredehoeft, 2002). For example, assume a well is installed in an aquifer that drains to a lake. As soon as the pump is turned on, it is the local hydrogeology, which includes but is not limited to recharge (e.g., discharge, transmissivity, pumping rate), that determines the dynamic response of the aquifer (Bredehoeft, 2002). Further, even if we assume that the water table after pumping remains constant and is therefore sustainable from the perspective of human water use, if discharge to the lake is diminished it may not be sustainable from the perspective of environmental water use (Saito et al., 2021). Scanlon et al. (2002) also note that aquifer recharge rates are difficult and expensive to measure, which limits both the evaluation and improvement of recharge estimates for the continental US.

Ideally, we would have used continental-scale modeling to determine groundwater use sustainability. However, data on critical aspects of those groundwater systems (e.g., permeability, pumping rates) are limited (Jasechko et al., 2021). Therefore, we create four sustainable groundwater use scenarios based on effective recharge estimates, hereafter recharge, for the United States published by Reitz et al. (2017). Reitz et al. (2017) developed a closed water budget, which includes precipitation, irrigation, quickflow, and evapotranspiration, to estimate recharge across the continental United States. To assess the sensitivity of our results to choice of recharge estimate, we repeated our calculations using a second recharge estimate for the United States published by Wolock (2003). Wolock (2003) estimated recharge by multiplying a grid of base-flow index values by mean annual runoff values. While the Wolock recharge estimate relied on thirty years of data (1951–1980), Reitz et al. (2017) used a more recent but shorter data set (2000–2013).

For the most optimistic scenario, sustainable groundwater use equals recharge (precipitation minus quick runoff and evapotranspiration from natural vegetation and crops). Consistent with Bredehoeft (2002), we also consider three less optimistic scenarios in which safe aquifer yield, and therefore sustainable groundwater use, is set to 75%, 50%, and 25% of recharge.

The impacts of reducing groundwater extraction on agricultural production can be addressed using a spatially explicit, process-based crop model. Process-based crop models can simulate the impacts of climate and management practices on agricultural production at field to global scales (Asseng et al., 2013; Elliott, Kelly, et al., 2014; Piontek et al., 2014; Rosenzweig et al., 2014). To simulate areas larger than a field, process-based crop models are run over multiple grid cells. For each grid cell, the model evaluates daily weather data, as well as information on soil properties, management, and crop varieties. In this study, we used a parallel and gridded implementation

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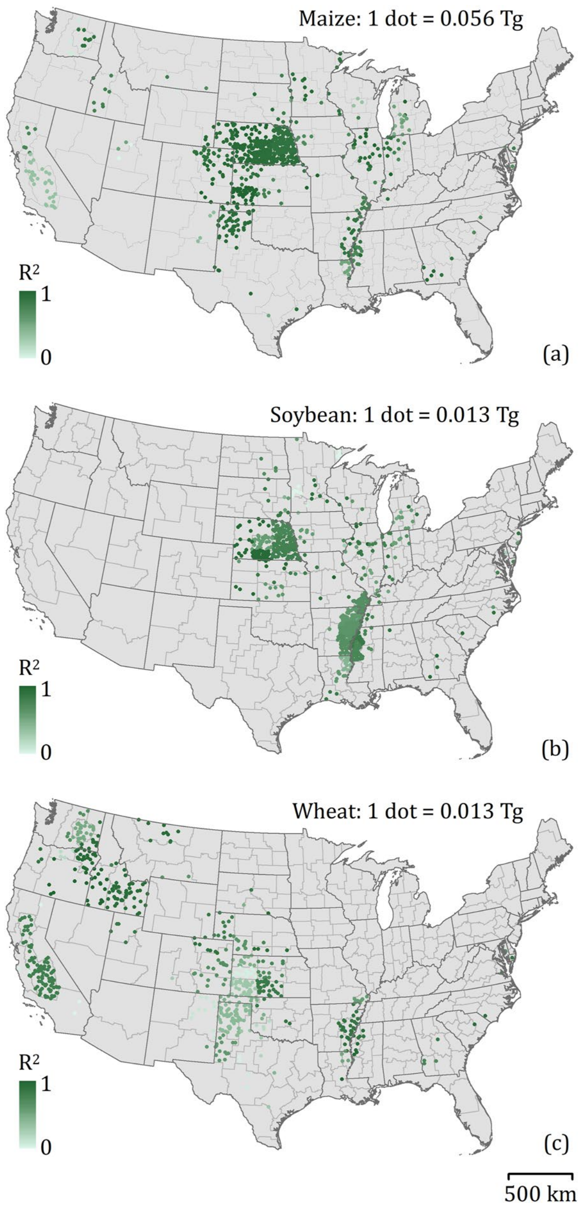

Figure 1. Coefficient of determination (R^2) for simulated and observed county level production by agricultural district for (a) maize, (b) soybean, and (c) winter wheat. Color intensity shows R^2, and dot density shows the amount of production in each agricultural district.

of the Decision Support System for Agrotechnology Transfer software (pDSSAT; Elliott, Kelly, et al., 2014; Hoogenboom et al., 2012; Jones et al., 2003), which contains a collection of process-based crop models.

Irrigation is critical to US agricultural production, yet unsustainable, and the impacts of reducing water use are largely unknown. In this manuscript, we calibrate and evaluate a gridded, process-based crop model, and use it to assess the effects of sustainable water use on irrigated production of maize, soybean, and winter wheat across the contiguous US (Figure 1). We further test the sensitivity of these effects to sustainable groundwater use scenarios to determine the range of possible shifts in irrigated agricultural production that would result from using water sustainably.

2. Materials and Methods

2.1. Modeling Approach

We simulated maize, soybean, and wheat yields on a 5 arc-minute grid (approximately 9 km at the equator) at a daily time step over a period of five years (2008–2012) using the Cropping System Models (CSMs) CERES-Maize (Jones et al., 1986), CROPGRO-Soybean (Boote et al., 1998; Wilkerson et al., 1983), and CERES-Wheat (Ritchie & Otter, 1985), respectively. At the time when the data for these simulations were assembled, this was the period with all necessary data available. Simulations were conducted on the Dartmouth Discovery Cluster using the Decision Support System for Agrotechnology Transfer (DSSAT), a widely used biophysical modeling platform that contains a suite of CSMs capable of simulating more than 42 crops including all major staple crops (Hoogenboom et al., 2017; Jones et al., 2003). The CSMs contained in DSSAT are point-based biophysical models that run on a daily time step and simulate crop growth and development as a function of weather, detailed soil profiles, cultivar specific parameters, and farm management. We ran gridded simulations of DSSAT using the parallel System for Integrating Impact Models and Sectors (pSIMS; Elliott, Kelly, et al., 2014), which has been applied to climate change and sustainability assessments across large regions and the world (Elliott, Deryng, et al., 2014; Elliott et al., 2013; Glotter & Elliott, 2016; Piontek et al., 2014; Rosenzweig et al., 2013, 2014).

2.2. Input and Calibration Data

Model input data sources are summarized in Table S1 in Supporting InformationS1. Weather data included incoming solar radiation, maximum and minimum temperatures, and precipitation. We used soil information for eight soil horizons in each grid cell, with attributes including bulk density, organic carbon, pH, and water release curve characteristics. The initial conditions and parameters, including crop specific parameters that simulate different cultivars, were those used by Glotter and Elliott (2016). Crop specific land use was obtained from the USDA Cropland Data Layer (CDL; Johnson & Mueller, 2010; Torbick et al., 2018). USDA-CDL land use data were further classified into irrigated and non-irrigated area using the Moderate Resolution Imaging Spectoradiometer (MODIS) Irrigated Agriculture Dataset for the United States (MIrAD-US; Pervez & Brown, 2010). All irrigated grid cells from each crop were simulated irrigated and rainfed to calculate irrigation water use efficiency (see below). The DSSAT irrigation algorithm does account for growing season rainfall throughout the study, as it triggers irrigation based on soil water status (Lopez, Winter, et al., 2017). In this study, irrigation was automatically triggered when 20% of the soil water holding capacity was depleted.

2.3. Model Calibration

We calibrated the model in two steps: first adjusting evapotranspiration (ET) based on an independent ET data source, and then calibrating yield using county-level measurements from NASS. In DSSAT, ET is computed using an implementation of the FAO-56 crop coefficient equations (Allen et al., 1998), which estimate crop ET as a crop-type-dependent fraction of potential ET. To assess the reliability of these estimates, DSSAT ET was compared to remotely sensed ET data from the Atmosphere-Land Exchange Inverse (ALEXI) model (Anderson et al., 2007). ALEXI uses the morning surface temperature increase retrieved with the Geostationary Operational Environmental Satellites in a surface energy balance algorithm to estimate surface energy and water fluxes at a 5 km resolution over the continental United States. Using a spatial disaggregation technique, ALEXI output has been evaluated with flux tower measurements, yielding typical root mean square errors of 1.0 and 0.4 mm d^{-1} at daily and seasonal time scales, respectively (Anderson et al., 2018). ALEXI output was aggregated over time (growing season defined as planting to harvest) and space (5 arc-minutes) to match pDSSAT simulations. In pDSSAT, the length of the growing season varies by crop, variety, and environmental factors such as photoperiod and thermal time, as described in Jones et al. (2003). Additionally, since 5 arc-minute grid cells may contain several sources of ET, including water bodies, natural vegetation, and various crops, we compared pDSSAT simulations only against aggregated ALEXI cells covered by at least 50% of the crops simulated. We find a relatively small percent bias (4%) between pDSSAT and ALEXI ET, which suggests that pDSSAT ET is reasonably simulated. While there are uncertainties in the ALEXI ET product, because it does incorporate observations by assimilating satellite temperatures to infer ET, we chose to adjust pDSSAT daily evapotranspiration by 4% through a daily potential evapotranspiration multiplier.

The benchmark for yield calibration was county-level yearly yield data reported by USDA NASS (irrigated and rainfed; USDA-NASS, 2017). Crop photosynthesis at the agricultural district level was calibrated to improve model simulations of yield using an ordinary least squares approach. Next, we evaluated the calibrated model against USDA NASS county-level production using a leave-one-out cross validation approach (Table S2 in Supporting Information S1). Across the US, the correlation between simulated and observed county-level production over both space and time is high for all crops, with R^2 values of 0.94, 0.91, and 0.82 for maize, soybean, and wheat, respectively (Table S2 in Supporting Information S1). Finally, evapotranspiration was re-evaluated against ALEXI ($R^2 = 0.68$; Figure S1 in Supporting Information S1), as evapotranspiration was altered by the calibration of yield. Cropped area within pDSSAT is accurate relative to USDA NASS data at the county level, with R^2 values for maize, soybean, and wheat of 0.95, 0.96, and 0.88. The correlations between pDSSAT simulations of maize, soybean, and wheat yields and NASS measurements over time are 0.54, 0.52, and 0.37. The bias in mean yield at the national level across years is below 10% for all crops, with maize simulated best, as it had the lowest bias and uncertainty, and winter wheat simulated worst, as it had a larger bias and the largest bias standard deviation (Figure S2 and Table S2 in Supporting Information S1). The relatively poor simulation of wheat is likely because it does not tend to dominate the landscape as much as soybean and corn, and therefore the area covered by wheat is a relatively limited fraction of grid cells (Hansen & Jones, 2000). The performance of pDSSAT is comparable to crop model performance for field-scale agricultural experiments (Lopez, Erickson, et al., 2017; Lopez, Winter, et al., 2017). Text S1 in Supporting Information S1 provides additional details on the calibration and evaluation of pDSSAT evapotranspiration and yield.

The modeling approach used to simulate maize, soybean, and wheat across the US is robust for most agricultural districts, with coefficient of determination between simulated and observed county-level agricultural production over space and time generally higher than 0.5 for all three crops, both rainfed and irrigated (Figure 1). Typically, pDSSAT is more accurate for all crops in high producing areas, such as the Midwest and the Mississippi Valley. This increase in accuracy is likely due to the dominance of the crop on the landscape and the spatial resolution of pDSSAT. For these high producing agricultural areas, the 5 arc-minute grid cells used for the simulations provide a better representation of the environment in which the crops are growing than in regions where the agricultural area covers a relatively limited fraction of the grid cell (Hansen & Jones, 2000). The accuracy of simulated production is notably higher for maize and soybean than winter wheat in agricultural districts across the US, except for California. Like mean yield bias, less accurate pDSSAT simulations of wheat in terms of R^2 and RMSE are also likely a result of a smaller fraction of grid cells cultivated as wheat (Hansen & Jones, 2000). The geographic distribution of the coefficient of determination for soybean is relatively uniform, while correlations for winter

wheat are highest in Idaho, California, and the Mississippi Valley, and lowest across southwestern Kansas and northern Texas (Figure 1).

A final model evaluation was conducted to assess the performance of the simulations at the district level for irrigated production only, because district-level irrigated production is the focus of our analysis. We also found strong correlations between pDSSAT and USDA NASS data in this evaluation, with R^2 values of 0.96, 0.97, and 0.81 for maize, soybean, and winter wheat, respectively. District level RRMSE values, 44%, 19%, and 90% for maize, soybean, and winter wheat production, respectively, were also very similar to county level production RRMSE values (Table S2 in Supporting Information S1). However, percent biases for the district-level irrigated simulations were higher, with values of −27%, −8%, and 28% for maize, soybean, and wheat production, respectively.

2.4. Sustainable Irrigation Water Use

We calculate sustainable irrigation water use by first determining the amount of groundwater that can be used sustainably for irrigation in each agricultural district (*GWs*). Then, adding surface water to *GWs*, we quantify the total amount of sustainable water available to irrigate each crop within each district (WU_S). Finally, we estimate the total production change, per crop and district, from limiting irrigation water use to WU_S.

GW_S depends on aquifer recharge, total groundwater extraction, and the sustainable groundwater use scenario (100%, 75%, 50%, and 25% of recharge). We estimated GW_S at the district level using the following equation:

$$\mathrm{GW}_S = \frac{\mathrm{GW}_T}{E} * R * \mathrm{AqY} \tag{1}$$

where, GW_T is the groundwater used for irrigation reported by the USGS for that district (Kenny et al., 2009; Maupin et al., 2014), R is estimated average recharge rate between 2000 and 2013 from Reitz et al. (2017) aggregated to the district level, E is the total district groundwater extraction reported by the USGS (Kenny et al., 2009; Maupin et al., 2014), and AqY is given by the sustainable groundwater use scenario (i.e., 1, 0.75, 0.5, or 0.25 for the 100%, 75%, 50%, and 25% scenarios, respectively). All variables, except for AqY, were converted to m^3 of water prior to calculation.

Our calculation of sustainable irrigation water use for each crop consisted of two steps. We first determined the sustainable irrigation fraction (*SF*), which is the fraction of the total water used for irrigation (ground and surface) that comes from surface water and sustainable groundwater extraction. *SF* was calculated at the agricultural district level using the following equation:

$$\mathrm{SF} = \frac{\mathrm{SW} + \mathrm{GW}_S}{\mathrm{SW} + \mathrm{GW}_T} \tag{2}$$

where, *SW* is the district-level surface water used for irrigation reported by the USGS (Kenny et al., 2009; Maupin et al., 2014). We assume that sustainable groundwater extraction for irrigation is bounded by USGS groundwater extraction for irrigation, and therefore do not allow *SF* to exceed a value of 1.

Finally, we estimated sustainable irrigation water use (WU_S) by crop and district using the following equation:

$$\mathrm{WU}_S = \mathrm{WU}_U * \mathrm{SF} \tag{3}$$

where, WU_U is the modeled water use for each crop and district, calculated by running pDSSAT with an assumption of unlimited water supply for each 5 arc-minute grid cell containing any irrigated area by crop. Sustainable irrigation water use was then multiplied by the area of irrigated agriculture for each crop to aggregate from grid cell to district level.

We define production losses as the difference between unsustainable and sustainable production. We calculate unsustainable production by multiplying simulated yield with unlimited water supply by irrigated area in each grid cell, and aggregating irrigated production from all grid cells across each district. We simulated sustainable production by removing the least water use efficient grid cells from the simulation until total water use was equal to WU_S. When appropriate, only a fraction of the last grid was removed. To determine which grid cells to remove, each was ranked by irrigation water use efficiency (*IWUE*). Sustainable production was obtained by limiting the

Table 1
Nationally Averaged Irrigated Production Losses From Sustainable Groundwater Use Over the Simulated Period (2008–2012)

	Production loss		
Sustainable groundwater use scenario	Maize	Soybean	Winter Wheat
100% Recharge	20%	6%	25%
75% Recharge	24%	9%	27%
50% Recharge	31%	15%	30%
25% Recharge	45%	37%	36%

Note. Production from simulated grid cells of maize (n = 47,100), soybean (n = 33,902), and wheat (n = 43,180) were aggregated for each sustainable groundwater use scenario to estimate national production.

irrigated crop production to only the grid cells with the highest *IWUE*. An example calculation of sustainable production is illustrated in Figure S3 in Supporting Information S1. We calculated irrigation water use efficiency for each grid cell with the following equation:

$$\text{IWUE} = \frac{Y_i - Y_r}{I} \tag{4}$$

where, Y_i is irrigated yield, Y_r is rainfed yield, and I is irrigation amount. DSSAT was run for each irrigated grid cell, rainfed and irrigated, to obtain Y_i and Y_r.

2.5. Uncertainty in Recharge Estimates

We assessed uncertainty in recharge estimates from Reitz et al. (2017) by calculating sustainable agricultural production by district using a second estimate of recharge from Wolock (2003). While there is a significant correlation between the Wolock (2003) and Reitz et al. (2017) recharge estimates ($R^2 = 0.35$, Figure S4a in Supporting Information S1), Reitz et al. (2017) estimates tend to be higher than those from Wolock (2003) as most districts fall below the 1:1 line. However, there is a significant number of districts where the Wolock (2003) estimate is higher. Geographically, recharge estimates are relatively similar across the High Plains (Figure S4b in Supporting Information S1). There are some districts where Reitz et al. (2017) estimates are much larger than Wolock (2003) in the Mississippi Valley, and some districts where Wolock (2003) estimates are large compared to Reitz et al. (2017) in the western states of California, Oregon, Washington, and Idaho (Figure S4b in Supporting Information S1). This is qualitatively consistent with the trend of decreasing precipitation in western states (NOAA, 2020), as the observations that Reitz used to model recharge are more recent than the observations used by Wolock.

3. Results and Discussion

3.1. National Impacts of Sustainable Agricultural Water Use

We assessed the impacts of sustainable groundwater use on irrigated production of maize, soybean, and winter wheat in the US by examining the difference in production between pDSSAT simulations with unlimited groundwater and pDSSAT simulations with groundwater reduced to a sustainable level (see Materials and Methods). Nationally averaged, production losses for the most optimistic sustainable groundwater use scenario (100% recharge) for maize, soybean, and winter wheat are 20%, 6%, and 25%, respectively, and production losses for the least optimistic sustainable groundwater use scenario (25% recharge) for maize, soybean, and winter wheat are 45%, 37%, and 36%, respectively. The production losses for maize and wheat are higher than soybean for sustainable groundwater use scenarios of 50% recharge or more, but at the least optimistic sustainable groundwater use scenario soybean production drops dramatically (Table 1).

The distribution of maize production losses in the most vulnerable districts is bimodal (Figure 2), with some districts and years experiencing near complete production loss (70%–90%) even at the most optimistic sustainable groundwater use scenario, and other districts experiencing more modest losses (10%–30%). District and year combinations with no change in production for the most optimistic groundwater use scenario are excluded from Figure 2 to create a reasonable scale for production losses, as well as highlight changes in production losses for a consistent set of district-year combinations under increasingly pessimistic groundwater use scenarios. We assess the significance of changes in crop production distributions using a two-sided Wilcoxon rank sum test ($\alpha = 0.05$). Maize production losses are significant for the 25% ($p = 3.9 \times 10^{-4}$), 50% ($p = 0.0037$), and 75% ($p = 0.019$) recharge scenarios. Soybean production is only significantly lower than the unlimited groundwater use scenario for the least optimistic sustainable groundwater use scenario ($p = 0.037$), though even at more optimistic groundwater use scenarios some districts experience production losses of 70%–90%. Consistent with the nationally averaged losses, soybean is particularly sensitive to the sustainable groundwater use scenario, with relatively few districts experiencing losses at the most optimistic sustainable groundwater use scenario, but many more at the least optimistic (Table S5 in Supporting Information S1). In contrast, for districts that experience losses, winter wheat production is significantly different from the unlimited groundwater use simulations regardless of

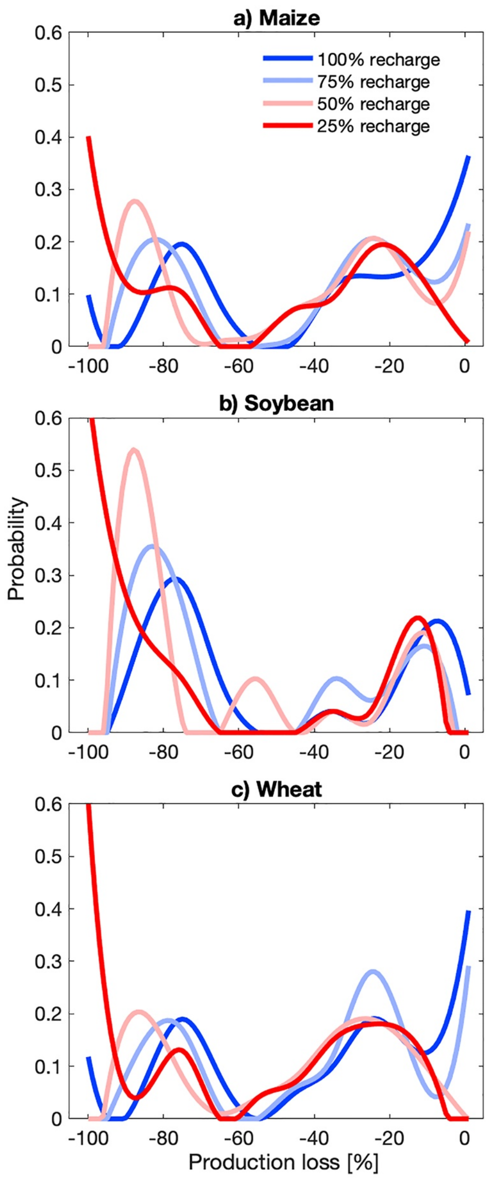

Figure 2. Production losses from sustainable groundwater use across the most impacted agricultural districts and years for (a) maize, (b) soybean, and (c) winter wheat with four different assumed sustainable groundwater use scenarios. Only districts with a difference between well-watered and sustainable production at the most optimistic sustainable groundwater use scenario (100% recharge), described in Table S5 in Supporting Information S1 (20 for maize, 8 for soybean, and 20 for wheat), are shown.

sustainable groundwater use scenario ($p = 2.8 \times 10^{-4}$ for 25%, $p = 1.5 \times 10^{-3}$ for 50%, $p = 4.9 \times 10^{-3}$ for 75%, $p = 0.02$ for 100%), and changes in the distribution of winter wheat losses are relatively insensitive to sustainable groundwater use scenario.

Together, these analyses highlight several key impacts of sustainable water use for irrigated agriculture at the national scale. First, even for the most optimistic sustainable groundwater use scenario, there are a number of districts with large (70%–90%) losses for each crop. Second, in relatively optimistic water restriction scenarios (groundwater use scenarios of 100% and 75% of recharge) the impacts on wheat and maize are large and the impacts on soybean are small. Finally, for the least optimistic sustainable groundwater use scenario (25% recharge) soybean losses dramatically increase and maize sustains the largest percentage production loss among the three crops considered.

3.2. Geographic Distribution of Sustainable Agricultural Water Use Impacts

Maize production losses are concentrated in southwestern Nebraska, western Kansas, northern Texas, and California for the most optimistic sustainable groundwater use scenario, but spread across most of Nebraska, intensify over western Kansas and northern Texas, and expand to the Mississippi Valley for the least optimistic sustainable groundwater use scenario (Figures 3a and 3b). Production losses for the most optimistic sustainable groundwater use scenario overlie the two most stressed aquifers in the United States: the High Plains and Central Valley. Qualitatively, these losses agree with future projections of irrigated maize production across the Missouri and California basins under water constraints (Turner et al., 2019). Irrigated maize production in the Midwest, including Iowa, Illinois, and Indiana, is largely unaffected. As expected, there is a correspondence between production losses and sustainable irrigation fraction (Figure 4, see Materials and Methods), with production losses first appearing in areas with low sustainable irrigation fractions, such as the High Plains and Central Valley, at groundwater use equal to 100% of recharge, and then expanding to regions with higher sustainable irrigation fractions, such as the Mississippi Valley, with decreasing access to recharge.

Soybean is mainly grown in more humid eastern areas of the US, including eastern Nebraska and the Mississippi Valley, where there is greater aquifer recharge (Reitz et al., 2017) and groundwater available for irrigation (Figure 4). Therefore, soybean production is less susceptible to reduced groundwater withdrawals for irrigation at more optimistic sustainable groundwater use scenarios (Figure 3c). However, at less optimistic sustainable groundwater use scenarios, agricultural water demand exceeds accessible recharge, and soybean production is significantly impacted (Figure 3d). Accordingly, losses for the most optimistic sustainable groundwater use scenario are largely restricted to southern Nebraska, while for the least optimistic sustainable groundwater use scenario losses cover extensive areas of eastern Nebraska and the Mississippi Valley. As with maize, irrigated soybean production is largely unaffected in the Midwest and production losses are generally greatest when the sustainable irrigation fraction is less than 0.5 (Figure 4).

In contrast to soybean, irrigated winter wheat production is located primarily in the more arid regions of the US with lower sustainable irrigation fractions (Figure 4), and therefore vulnerable to even modest irrigation reductions. For the most optimistic sustainable groundwater use scenario, production losses were split between the High Plains states of Nebraska, Kansas, and Texas, and western states of Washington, California, and Idaho (Figure 3e). Irrigated winter wheat is less sensitive to sustainable groundwater use scenario (i.e., production loss

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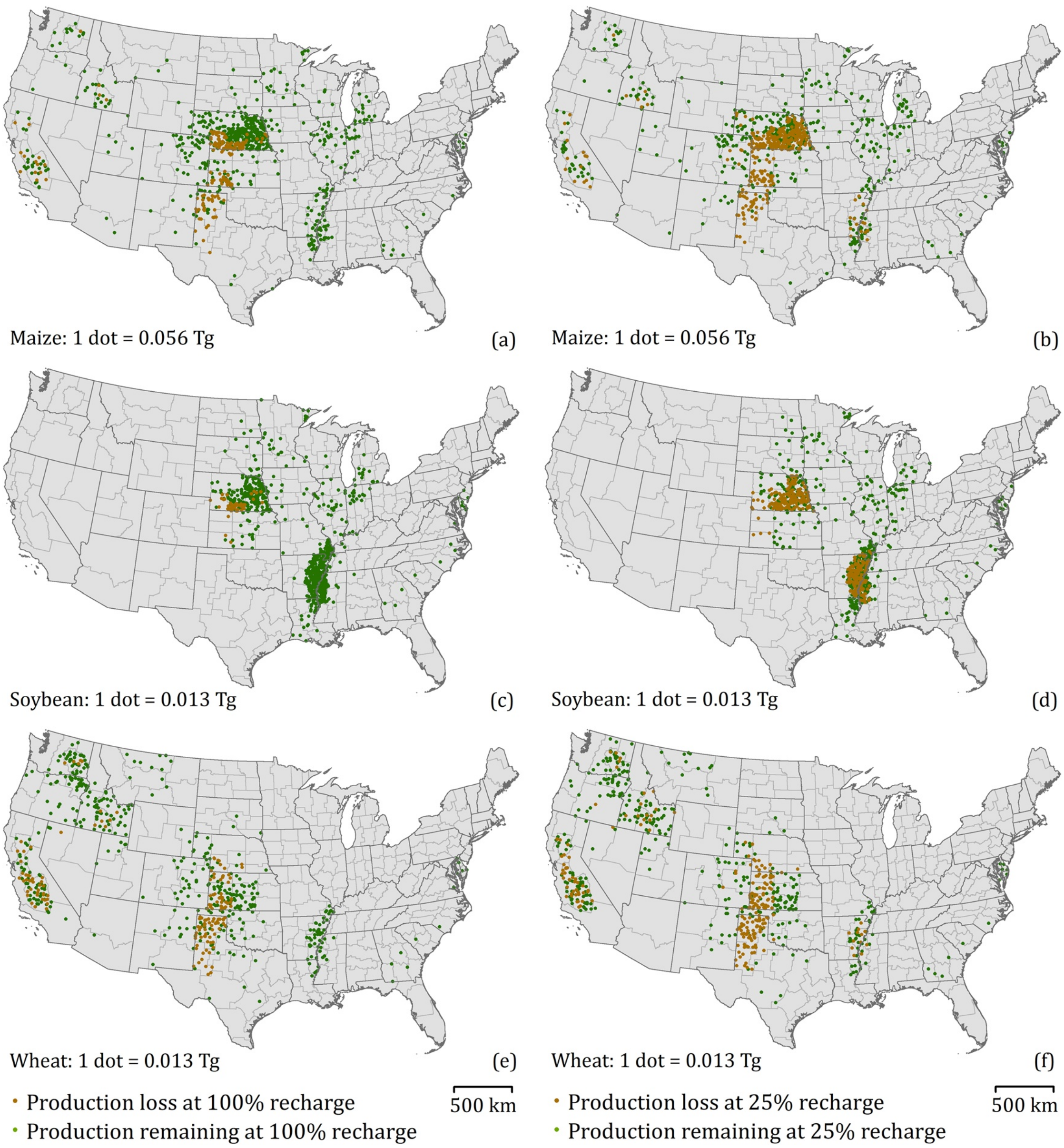

Figure 3. Spatial distribution of production losses from sustainable groundwater use by agricultural district with the most optimistic sustainable groundwater use scenario (100% recharge) and least optimistic sustainable groundwater use scenario (25% recharge) for (a), (b) maize, (c), (d) soybean, and (e), (f) winter wheat. All dots show total irrigated production, brown dots show production loss due to sustainable groundwater use, and green dots show sustainable production remaining.

difference between groundwater use equal to 100% recharge and 25% recharge) than maize and soybean. While losses do intensify for the least optimistic sustainable groundwater use scenario, there is a substantial amount of production that is insensitive even when groundwater use is set to 25% of recharge. This response is clear in Figure S5c in Supporting Information S1, which shows extensive production classified as red (production lost at 100% of recharge) and dark green (production remaining at 25% of recharge). Figure 3 and Figure S5c in Supporting Information S1 also highlight that compared to maize and soybean, fewer additional regions of irrigated winter wheat are affected by less optimistic sustainable groundwater use scenarios, and that the same regions experiencing losses at more optimistic sustainable groundwater use scenarios are further impacted at less optimistic groundwater use scenarios.

Aggregated across maize, soybean, and wheat, the most sensitive region of the US to groundwater restrictions is the High Plains. Five agricultural districts in this region show substantial yield reductions for all three crops

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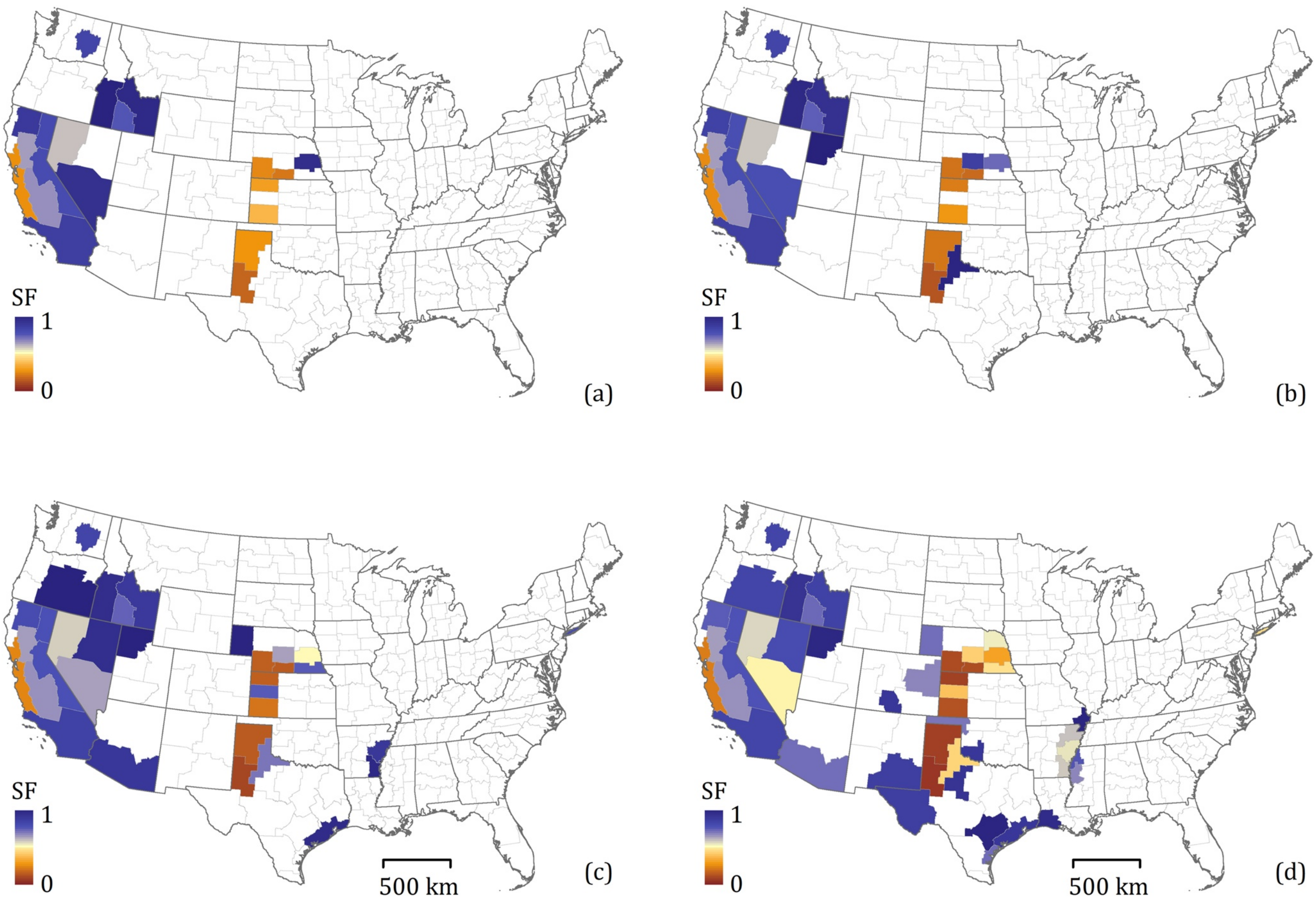

Figure 4. Spatial distribution of sustainable irrigation fraction (SF) at (a) 100% recharge, (b) 75% recharge, (c) 50% recharge and (d) 25% recharge. Blank districts have a SF of one or more. Blank districts have a SF of one or more. Values of one or more indicate no pressure from agricultural water use on aquifer sustainability, and values below one indicate unsustainable water use because extraction is higher than recharge.

(Figure 3) at the most optimistic sustainable groundwater use scenario: district 11, located in northern Texas; districts 10 and 30 in northwest and southwest Kansas, respectively; and districts 70 and 80 in southern Nebraska (USDA-NASS, 2007). These districts, all located over the High Plains Aquifer, have three common attributes: high irrigated agricultural area (combined the districts represent 11% of national irrigated agricultural area), a large proportion of groundwater extraction for irrigation (between 94% and 97%; Maupin et al., 2014), and groundwater extraction rates more than three times the aquifer recharge rates (4.0 times for district 11, 3.6 times for district 10, 3.2 times for district 30, 5.4 times for district 70, and 7.5 times for district 80; Reitz et al., 2017). This reinforces previous studies that have identified the High Plains Aquifer as particularly vulnerable to changes in groundwater extraction rates for irrigation (Famiglietti, 2014; Reitz et al., 2017; Scanlon et al., 2012). California, overlying the Central Valley Aquifer, also experiences large reductions in maize and winter wheat yields; however, specialty crops dominate irrigated agriculture in California, making production of, and therefore production losses of, staple crops smaller than in the High Plains.

The Mississippi Valley, in contrast, is relatively unaffected by sustainable groundwater use. Only six districts in the Mississippi Valley have both substantial corn and soybean production losses at the least optimistic sustainable groundwater use scenario: district 90 in Missouri, district 30, 60, and 90 in Arkansas, and districts 10 and 40 in Mississippi (Figure 3). At more optimistic sustainable groundwater use scenarios, production in these districts is practically unchanged. While these districts also have large overall irrigated agricultural area (combined the districts represent 13% of the national irrigated agricultural area) and utilize most of the groundwater they extract for irrigation (between 87% and 98%; Maupin et al., 2014), their groundwater extraction rates are less than their aquifer recharge rates (0.26 times for district 90, 0.48 times for district 30, 0.60 times for district 60, 0.54 times for district 90, 0.36 times for district 10, and 0.4 times for district 40; Reitz et al., 2017). Finally, across the upper

Midwest, including Minnesota, Wisconsin, Iowa, Illinois, Indiana, and Michigan, irrigated production of maize and soybean is largely unaffected (Figure 3). Agricultural districts in these states are more humid and predominantly rainfed.

3.3. Production Loss Uncertainty Due to Recharge Rate Estimates

The nationally averaged production losses due to sustainable groundwater use calculated with Wolock (2003) recharge estimates are larger for soybean, lower for wheat, and remarkably similar for maize compared to nationally averaged production losses due to sustainable groundwater use calculated with Reitz et al. (2017) recharge estimates (Table 1 and Table S3 in Supporting Information S1). The differences in soybean production losses are explained by the higher recharge estimates of Reitz et al. (2017) over the Mississippi Valley, where a large portion of the irrigated soybean production in the US is concentrated. Conversely, recharge estimates of Wolock (2003) are larger than the recharge estimates of Reitz et al. (2017) in the western states where a substantial proportion the winter wheat production is located, resulting in smaller production losses of winter wheat nationally. Irrigated maize production losses are similar regardless of recharge estimate used as maize is concentrated in the High Plains where Reitz et al. (2017) and Wolock (2003) estimates agree (Figure S4b in Supporting Information S1).

Despite the similarities between recharge estimates of Reitz et al. (2017) and Wolock (2003), there remains considerable uncertainty in accessible aquifer recharge across irrigated areas. A fundamental limitation of Reitz et al. (2017) and Wolock (2003) is the lack of an explicit simulation of the complex interactions between groundwater and surface water. Flow between surface water and groundwater can be a major component of the water budget (Winter et al., 1998). In a recent study, Jasechko et al. (2021) showed that most streams likely contribute to aquifer recharge (i.e., flow from surface water to groundwater). However, this flow can also be reversed (i.e., flow from groundwater to surface water), often in steeper headwaters (Jasechko et al., 2021), highlighting the complexity of interactions between surface water and groundwater. Further, while Reitz et al. (2017) and Wolock (2003) are substantial advances in quantifying recharge rates across the United States, both methods were largely evaluated using data from non-irrigated areas, which adds further uncertainty to their application over heavily irrigated regions.

We therefore used a wide range of sustainable groundwater use scenarios to account for this considerable uncertainty, as well as the varied definitions of sustainable groundwater use. For example, pumping at 25%–50% of recharge is likely to increase groundwater levels in many depleted aquifers, which would potentially lead to less restrictions and avoided production losses. However, if environmental flows play an important role, the groundwater level increase would begin to level off as those flows increase. In areas with considerable depth to water, it would likely be decades before environmental flows have an impact. To what extent water levels would rise and where, and complicating factors such as post-development aquifer changes, environmental flows, and vulnerable shallow domestic wells, make narrowing the range of recharge accessible, and in turn the uncertainty in our findings, difficult (Bredehoeft, 2002; Saito et al., 2021).

4. Conclusion

We show that sustainable agricultural water use, simulated by limiting groundwater use to available recharge, reduces US production of irrigated maize, soybean, and winter wheat by 20%–45%, 6%–37%, and 25%–36%, respectively. Winter wheat and maize production are most vulnerable at optimistic sustainable groundwater use scenarios, while for the least optimistic sustainable groundwater use scenario maize is most vulnerable, followed by soybean and winter wheat. The largest production losses occur across the High Plains states, especially Nebraska, western Kansas, and northern Texas. This region is heavily reliant on groundwater from the High Plains Aquifer, and generally cannot support rainfed agriculture. California, drawing from the Central Valley Aquifer, and other western states also experience reduced production, although they devote less area to maize, soybean, and winter wheat. Production losses extend to the Mississippi Valley, especially for soybean, at less optimistic sustainable groundwater use scenarios. Using an alternative estimate of recharge, we find general agreement in production losses due to sustainable irrigation water use. However, with the alternative estimate of recharge soybean is the most sensitive (20%–51%) to sustainable irrigation water use, followed by maize (20%–34%) and winter wheat (14%–28%).

We note that in our analysis, technology, management, and the fraction of total irrigation water from groundwater are held fixed as water supply is reduced. There are a variety of adaptations such as increased aquifer monitoring and management, irrigation efficiency, crop switching, reduced soil evaporation, and deficit irrigation that can decrease agricultural water use (Butler et al., 2018; Davis et al., 2018; Fereres & Soriano, 2007; Grafton et al., 2018; Rost et al., 2009). For example, Deines et al. (2019) found that irrigators in the Sheridan-6 Local Enhanced Management Area (LEMA) were able to decrease groundwater use by 31% through a combination of improving water use efficiency (22%), switching crops (6%), and reducing irrigated area (3%). Perhaps the most striking result of Deines et al. (2019) is that most of the irrigation reductions came from improving irrigation water use efficiency, which was achieved in part through better soil moisture monitoring. This is consistent with modeling studies that show optimizing irrigation based on growth stage specific soil moisture thresholds can significantly improve irrigation water use efficiency (Lopez, Winter, et al., 2017). While coordinated groundwater conservation efforts such as LEMA are rare (Deines et al., 2019), analyzing possible responses to reduced groundwater supplies is an important line of future research that would push beyond our simplifying assumption that the only strategy for decreasing water use is reducing production via fallowing.

We also focus on staple crops, which account for most of the irrigation across the Central US, but not in the western US where specialty crops are substantial and often the dominant users of agricultural water. In addition, international food trade has the potential to offset some of the negative impacts of irrigation water supply shortages (Liu et al., 2014). Agricultural water sustainability is just one facet of an evolving national food production system that is intricately linked to global markets. Climate change will have major impacts on irrigated crop yields through changes in plant water use efficiency (Guo et al., 2010; Keenan et al., 2013), temperature (Ray et al., 2015; Zhao et al., 2017), and water supply (Haddeland et al., 2014). For example, Elliott, Deryng, et al. (2014) found greater production losses running global gridded crop models without CO_2 effects than with CO_2 effects, where enhanced levels of CO_2 increased simulated plant water use efficiency. Elliott, Deryng, et al. (2014) further identified currently rainfed agricultural areas that had the potential for irrigation, offsetting losses from irrigated regions that were no longer viable, but requiring substantial investment. Liu et al. (2017) concluded that a projection of increased precipitation makes some currently unsustainable irrigated agriculture in the Central US more sustainable by the year 2050, though they only used one climate change scenario and future summer drying is generally predicted for the Central US (Hayhoe et al., 2018). While not directly comparable, our results are consistent with Jain et al. (2021), who found that groundwater depletion in India, which also contains extensive water-stressed and heavily irrigated agricultural areas, will experience a substantial reduction in cropping intensity of 20% nationwide and 68% in groundwater-depleted areas.

Sustainable irrigated agriculture is vital to ensuring US food security and supporting the broader global food system. We note that a substantial portion of the US maize production (between 34% and 39% over the past five years) is used for fuel ethanol (DOE, 2021). This implies that reductions in food production from maize will not directly scale with reductions in maize production, and that reductions in maize production will have an additional impact on the ethanol industry.

Our study highlights the range of potential impacts on irrigated crops in the US from using water sustainably based on a physically constrained set of groundwater use scenarios. Our sustainable groundwater use scenarios, which linearly scale the amount of accessible recharge, could also represent the difference between immediate action to reduce groundwater consumption (most optimistic sustainable groundwater use scenario) and delaying action (least optimistic sustainable groundwater use scenario) until the viability of irrigation from the High Plains and Central Valley Aquifers is compromised (Scanlon et al., 2012). The latter scenario would not only have a devastating impact on heavily irrigated agricultural regions and even some areas not usually thought to be groundwater limited, but also reduce US agricultural productivity with serious repercussions for the global food supply.

Data Availability Statement

Model outputs and calibration parameters are available in the Dryad repository at https://doi.org/10.5061/dryad.cc2fqz65x. Datasets published in the literature used for this research as model inputs or for model evaluation are available through the references listed in Table S1 in Supporting Information S1. The Atmosphere-Land Exchange Inverse (ALEXI) evapotranspiration data is an intermediate research product available through Anderson

et al. (2007). A similar version of this data are publicly available from USGS: https://lpdaac.usgs.gov/products/eco3etalexiuv001/.

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